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Spatial Interactions in Tropical Deforestation: An application to the Brazilian Amazon

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Abstract

This paper investigates the mechanisms determining spatial interactions in deforestation, and its transmission channels, using data from Brazil. Our preliminary results confirm the hypothesis that deforestation in the Brazilian Amazon is characterized by complementarity, meaning that deforestation in a particular municipality tends to increase deforestation in its neighbors. We further show that cattle density, tend to be the most important factors determining the nature of spatial interactions between neighboring areas.

Key words: Deforestation, Brazilian Amazon, Spatial and Dynamic interactions

JEL codes: C21, O13, Q33

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1 Introduction

Despite global concerns over forest protection, tropical deforestation continues at an alarming pace. For instance, deforestation in the Brazilian Amazon is estimated at more than 5800 sq. kilometers in 2013, although a decreasing trend was observed in the last decade (INPE, 2013).[1]

There exists a vast literature on the determinants of deforestation; factors such as increased agricultural output prices, better agro-ecological conditions, lower input prices, better roads and infrastructure as well as technological progress have been shown to favor forest conversion (e.g. Kaimowitz and Angelsen, 1998; Barbier and Burgess, 2001; Andersen et al., 2002). Moreover, this literature has confirmed that forest conversion and land-use changes are phenomena that exhibit spatial patterns (e.g. Mertens et al., 2002; Pfaff et al., 2007; Robalino and Pfaff, 2012).

Spatial interactions in forest conversion can be of two types. In fact, deforestation in a given region can either increase or decrease forest conversion in neighboring areas. The empirical literature on deforestation has indeed provided examples of both types of interactions. For example, Robalino and Pfaff (2012) show a positive spatial contagion when looking at deforestation in Costa Rica; they observe that deforestation in one county favors deforestation in neighboring areas. In Amazon, several studies (Amin et al., 2014; Corrêa de Oliveira and Simões de Almeida, 2010; Aguiar et al., 2007; and Igliori, 2006) have addressed this issue. These studies highlight a strong influence (positive) of spatial interactions on the dynamics of deforestation in the region. However, these studies, based on cross-sectional data, do not take into account the dynamic aspects of deforestation. Controlling for dynamic aspects is essential as it is now well established that deforestation is a dynamic process, in which changes to key factors occurring in previous periods are likely to affect current conditions and, therefore, current decisions. For instance, areas that were previously partially cleared may be easier to access and deforest today. Similarly, public policies such as subsidized credit lines or colonization programs may take a few years to impact deforestation.

However, Pfaff et al. (2014) when applying matching methods to the investigation of impacts of protected areas (PAs) in the Brazilian Amazon, find lower deforestation rates around some PAs than would be expected without PAs. In the same vein, it has been shown that increased agricultural productivity and lower transport costs in one region may result in a concentration of activities in that same region, thus lowering pressure on forest in adjacent areas (e.g. Angelsen and Kaimowitz, 1998; Weinhold and Reis, 2008). Finally, the literature on forest protection and REDD has showed

[1] http://www.obt.inpe.br/prodes/prodes_1988_2013.htm, accessed on January 7th, 2014.

that policies promoting forest conservation in a given area might result in increased deforestation elsewhere (e.g. Angelsen, 2008).

The first aim of this paper is to investigate the mechanisms behind spatial interactions and the conditions under which each type of interaction, positive or negative, may materialize, while jointly controlling for dynamic aspects. The second objective is to analyze the impact of policies to fight against deforestation on the nature of spatial interactions. We will focus particularly on Action Plan for the Prevention and Control of Deforestation in the Legal Amazon.

Improving our understanding of the mechanisms behind these different types of spatial interactions should lead to more efficient forest protection measures (Amin et al., 2014).

We first present a simple theoretical setting that allow us to investigate the determinants of spatial interactions in tropical deforestation. In Section 3, we estimate these interactions using a model that includes both spatial and dynamic correlations. The dynamic aspect is represented by the use of lagged values of the main explanatory variables. Regarding the spatial interactions, we build a spatial weight matrix, in the spirit of Anselin (2003), that links land-use changes in a given county to land-use changes elsewhere as an inverse function of the distance between the two locations. In particular, by allowing us to disentangle direct and indirect spatial interactions, our empirical model enables the investigation of the economic factors determining the type of spatial interaction that materialize in different regions. Section 4 reports and discusses the results. Concluding remarks are given in Section 5.

2 A theoretical spatial analysis of deforestation

We first present a general model of spatial interactions, before giving a more specified approach of spatial distribution.

2.1 General spatial model

We consider here n Legal Amazon counties, each illustrated by a representative agent. Each municipality chooses its level of deforestation in order to maximize its utility:

$$\max_{D_i} U_i(D_i, X_i, \sum_{j \neq i} \rho_{ij} D_j, \sum_{j \neq i} \beta_{ij} X_j). \tag{1}$$

municipality i's utility obtained by clearing D_i hectares of forest is assumed to depend on its exogenous characteristics X_i, which encompass outside opportunities, human development, distance to the main markets, and other economic factors likely to affect its demand for forest conversion. Additionally, it depends on the deforestation level of neighboring counties D_j and intensity of interactions ρ_{ij} to those neighbors. It can also depend on i's neighbors exogenous variables X_j and interactions intensity β_{ij}.

As mentioned in the Introduction, two kinds of interactions may exist between counties. First, under what we call a *complementarity* situation, observing a high deforestation level on its neighbors' land may incite a municipality to increase its own level of deforestation. This may be the case if the neighbors show that forest conversion fosters local development. Second, under a *substitutability* situation, observing a high level of deforestation in neighbors may lead municipality i to reduce its own deforestation. This can be the case if a neighbors' deforestation increase municipality i's outside opportunities or if it decreases its benefits from deforestation. Similarly, substitution may occur if deforestation agents migrate from municipality i to the surrounding areas.

The First-Order Conditions of problem (4) implicitly give the optimal level of deforestation D_i^* of municipality i, which depends on its own characteristics, its neighbors best response D_j^* and characteristics X_j:

$$D_i^* = D_i(X_i, \sum_{j \neq i} \rho_{ij} D_j^*(X_j), \sum_{j \neq i} \beta_{ij} X_j). \tag{2}$$

From this very simple model, it is possible to infer how deforestation in a particular municipality is influenced by its neighbors' deforestation. Proposition 1 below summarizes this.

Proposition 1: *municipality i's deforestation level will tend to be closer to its neighbors' if both have the same exogenous characteristics. Moreover, observing a high level of deforestation in the neighborhood will tend to decrease municipality i's deforestation in a* substitutability *situation, while it will tend to increase it in a* complementarity *situation. Similarly, a characteristic X_j will tend to decrease i's deforestation if it is a factor of* substitutability*, and to increase i's deforestation if it is a factor of* complementarity*.*

In the following, we present a spatially-explicit version of this simple model, that allow us to further analyze the role of spatial interactions in determining deforestation levels.

2.2 A Simple Spatial Game of Deforestation with Multiple Counties

One of the objective of the paper is to understand how spatial distribution can affect interactions between counties. In this section, therefore, we will present our intuitions relying on a simplified specified version of our previous model.

We consider here the potential implications of the two types of spatial interactions presented above, using a specified version of the previous model.[2]

For simplicity, we restrict the analysis to two types of counties: if $X_i = \overline{X}$, municipality i gets higher relative direct benefits from deforestation, meaning that deforestation is highly profitable and/or its outside opportunities are low; if $X_i = \underline{X}$, municipality i gets low relative direct benefits from deforestation, meaning that deforestation provides low profit and/or its outside opportunities are high. We consider two types of spatial distribution of agents, that we called concentration and dissemination cases (see Figure B.1).

Regarding spatial interaction, we assume for simplicity that (1) they only matter trough exogenous characteristics (α_{ij}= 0), and (2) they only matter between direct neighbors, i.e., $\delta_{ij} \in]0;1]$ if i and j are direct neighbors, $\delta_{ij} = 0$ if not. Note also that interactions are small when δ_{ij} is close to 0 and important if it is close to 1.

Interactions with neighbors are determined by either *subsitution* or *complementarity* effects: in the first case, a neighbor with $\overline{X}$ (resp. $\underline{X}$) characteristics will have a large (resp. small) negative impact on municipality i's return from deforestation; in the second one, it will have a large (resp. small) positive impact.

Finally, we apply a simple form of quadratic utility function:

$$U_i(D_i, X_i, \sum_{j \neq i} \delta_{ij} D_j) = (aX_i \pm \sum_{j \neq i} \beta_{ij} X_j) D_i - \frac{1}{2} D_i^2 \tag{3}$$

The optimal deforestation level of any municipality i is corresponds to the equalization of marginal benefit and marginal cost of deforestation:

$$D_i^* \quad = \quad aX_i \pm \sum_{j \neq i} \beta_{ij} X_j. \tag{4}$$

This specification allows us to highlight three factors: ($\imath$) the level of interaction, which may be high or low; ($\imath\imath$) spatial distribution, as counties of the same type may be either concentrated or disseminated; ($\imath\imath\imath$) *substitutability* or *complementarity* of interactions.

[2] The value of the parameters are given in the Appendix.

This simple setting provides several insights. By looking at illustrative Figures C.1, D.1, E.1 and F.1 (in the Appendix), it appears that a higher level of spatial interactions tends to increase overall deforestation in a *complementarity* situation, while it decreases it in a *substitution* situation. Moreover, in a *complementarity* situation (see Figures C.1 and D.1), deforestation from $\overline{X}$ counties is higher when counties of the same type are concentrated rather than disseminated, while deforestation from $\underline{X}$ counties is lower (higher) when counties of the same type are concentrated (disseminated). In contrast, in a *substitutability* situation (Figures E.1 and F.1), $\overline{X}$ counties have lower levels of deforestation when concentrated (compared to the disseminated case), while $\underline{X}$ counties have higher deforestation if concentrated. These insights are summarized in the Proposition below.

Proposition 2: *Concentration increases (resp. decrease) deforestation from* $\overline{X}$ *(resp.* $\underline{X}$*) counties in a* complementarity *situation, while it tend to decrease (resp. increase) it in a* substitution *situation. Dissemination decreases (resp. increases) deforestation from* $\overline{X}$ *(resp.* $\underline{X}$*) counties in a* complementarity *situation, while it tend to increase (resp. decrease) it in a* substitution *situation.*

Overall, therefore, we are interesting in the next section in the understanding of the main channels of spatial interactions between counties from the Brazilian Amazon, as well as the spatial distribution of the variables that we will underline.

3 Investigating spatial interactions in the Brazilian Legal Amazon deforestation process

3.1 Empirical methodology

The general spatial dynamic panel data model related to our theoretical model can be written as:

$$\begin{aligned} D_{it} &= \alpha D_{i,t-1} + \rho W_1 D_{jt} + \beta_1 X_{it} + \beta_2 W_1 X_{jt} + \nu_{it}, \\ \nu_{it} &= \mu_i + \gamma_t + \lambda W_2 \nu_{jt} + \epsilon_{it}, \end{aligned} \tag{5}$$

where D_{it} is the level of deforestation for every municipality ($i = 1, ..., N$) in the sample at time t ($t = 1, ..., T$), W_1 and W_2 are non-negative spatial weight matrices, and X_{it} is a $N \times K$ matrix of explanatory variables. $D_{i,t-1}$ and $W_1 D_{jt}$ are respectively the level of deforestation lagged in time and in space. Finally, ν_{it} is the overall error term of the model which can be divided into four parts: μ_i represents the individual (fixed or random) effects, γ_t the time-period specific effects, $W_2\,\nu_{jt}$ is the error term lagged in space and ϵ_{it} is the i.i.d distribution term.

To determine the best specification for our data, we estimate six variants of the general spatial model:

- a Spatial Error Model (SEM) when $\alpha = \rho = \beta_2 = 0$: in this case, the municipalities tend to have the same deforestation behavior because they have unobservable characteristics that are spatially autocorrelated.

- a Spatial Autoregressive Model (SAR) when $\alpha = \beta_2 = \lambda = 0$: captures the endogenous interaction effects which means that the deforestation level for one municipality is jointly determined with that of neighboring municipalities.

- a Spatial Durbin model (SDM) obtained when $\alpha = \lambda = 0$: in this model we have both endogenous interaction effects among the deforestation level (endogenous variable) and exogenous interaction effects among the explanatory variables.

- a Spatial Autocorrelation Model (SAC) when $\alpha = \beta_2 = 0$: catures endogenous interaction effects and interaction among spatially autocorrelated error terms (omitted variables).

- a Dynamic Spatial Autoregressive Model (DSAR) when $\beta_2 = \lambda = 0$: takes into account endogenous interaction effects and the dynamic of deforestation (time lagged variable of deforestation).

- a Dynamic Spatial Durbin Model (DSDM) when $\lambda = 0$: captures the dynamic of deforestation over the time, endogenous interaction effects and exogenous interaction effects.

So as to select among the six alternative models estimated, we use the Bayesian Information Criteria (BIC) and the Akaike Information Criterion (AIC). The results, presented in Table I.1 (See Appendix), indicate that the DSAR and DSDM models are preferred to the alternative models according to both criteria. However, the AIC criterion prefers the DSDM model to the DSAR one, while the result is reversed according to the BIC criterion. To decide between these two nested models we apply the Likelihood Ratio Test. The corresponding statistic is 32.4, which allows us to reject (at the 1% level) the hypothesis that the coefficients of spatially lagged explanatory variables (β_2) are equal to zero. Hence, for our data, the best specification is DSDM model, i.e. when $\lambda = 0$ in model (5). In particular, this implies that we can abstract from correlated effects. This statistical result is consistent with economic theory of deforestation. Indeed, the rate of deforestation in neighboring municipalities can be seen as a signal of market potential production (agricultural and livestock) or as an alert on the adverse effects of deforestation. This can lead to complementarity or substitution effects between the decisions of deforestation (Robalino and Pfaff, 2012; Angelsen and Kaimowitz, 1998; Weinhold and Reis, 2008). Following recent developments in spatial econometrics (Fingleton, 2011; LeSage, 2014) the SDM are appropriate in this case. In addition, several studies have shown that deforestation is characterized by inertia phenomena (Andrade de S · et al., 2013). In other words, the time lagged level of deforestation is a determinant of current deforestation.

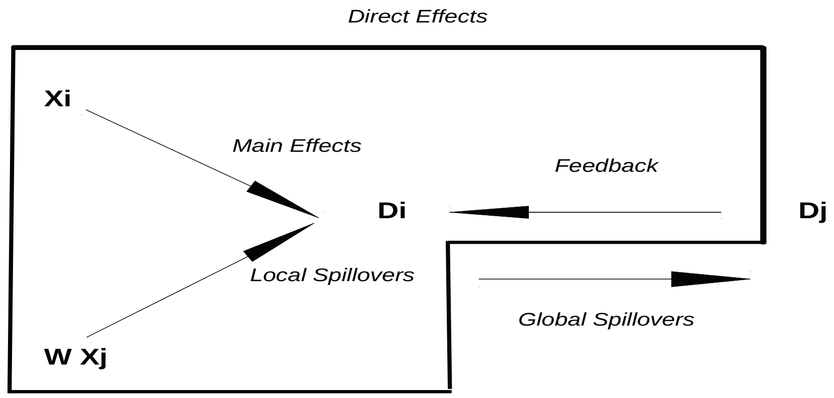
Additionally, we apply the Hausman test to determine whether a fixed or random effects version should be used. The test statistic χ^2 is equal to 58.09, so we reject the null hypothesis of independence between errors and explanatory variables and accordingly opt for a fixed-effects model. Table I.2 in the Appendix presents the results of DSDM model with both fixed effects and random effects.

Finally, using the DSDM model, we also estimate three specifications of the spatial weight matrices: an inverse distance matrix $(1/d)$, an inverse distance squared matrix $(1/d^2)$ and an inverse distance cubed matrix $(1/d^3)$, where a higher exponent of the distance implies stronger spatial interactions between a given MCA and its nearest neighbors. The spatial spillovers effects are more significants in the last model (with inverse distance cubed matrix). This expected result is related to the well-known first law of geography: " Everything is related to everything else, but near things are more related than distant things " (Tobler, 1970, p. 236). In the remainder of this paper, we discuss the results of this model.

To summarize, our reference model is a Dynamic Spatial Durbin Model (DSDM) with fixed-effects model and an inverse distance cubed matrix. Results from this specification are presented in the third column of Table 1. This specification allows to consider (i) the deforestation drivers X_{it} determining county i's deforestation (β_1); (ii) the general direction and intensity of spatial interaction, estimating endogenous effects (ρ); and (iii) local spillovers (β_2), represented by the parameters associated with spatially lagged independent explanatory variables, arise only in the neighboring MCA.

To better appreciate the effects of spillovers associated with variation in a particular explanatory variable, Lesage an Pace (2009) propose to estimate its estimated indirect effects which occur when endogenous effects are observed $(\rho \neq 0)$. For instance, in our case study, these effects measure the average impact of changes in an independent explanatory variable of MCA i on the deforestation

Figure 1: Spatial Effects



in all other MCA j. Indirect effects are global spillovers because they arise in all MCA, not just neighboring MCA.

Direct effects will allow us to analyse the impact of the variation of an independent explanatory variable of MCA i on the deforestation in MCA i. These effects also take into account the feedback effects arising from the change in the *ith* MCA's deforestation level on deforestation of neighboring MCA in the system of spatially dependent MCA. The total effect of a given explanatory variable is the sum of direct effects and indirect effects. The results of direct, indirect an total effects are presented in the Table 2. The various spatial effects described in this section are summarized in figure 1.

It is important to note that in the Spatial Durbin Model, the direct and indirect effects of a given explanatory variable depend both on the estimated parameter β_1 associated with this variable, and on the estimated coefficient associated β_2 with its spatially lagged value (Halleck Vega and Elhorst, 2012).

3.2 Dataset

We use a panel data set constituted of secondary data for all of Brazil's Legal Amazon counties for the years 2001-2010. For homogeneity issues, the municipal data is aggregated into 258 Minimum Comparable Areas[3] (MCAs). These constitute our units of observation, i. Tables G.1 and H.1 (see

[3]The list of Brazilian MCAs from 1970 to 2005 was provided by the Brazilian Institute of Applied Economic Research (*Instituto de Pesquisa EconÙmica Aplicada*, IPEA).

Appendix), respectively, present a description of the main variables used in the analysis and offer some descriptive statistics.

Deforestation data come from the geo-database of land use over the period 2001-2010 produced by the PRODES System of the Instituto Nacional de Pesquisa Espacial - INPE (National Space Research Center). The remaining land use data (cattle heads) were obtained from IBGE's Pesquisa Agricila Municipal (PAM) and Pesquisa Pecu · ria Municipal (PPM).

We also include GDP, percentage of agricultural GDP and population density as control variables. We used data on counties' resident population to compute GDP per capita and population density variables for our units of observation.

Finally, in 2004 the Brazilian government initiated a series of forest conversation measures via the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (*Plano de Acção para a Prevenção e o Controle do Desmatamento na Amazônia Legal*, PPCDAm). In particular, this program consisted in closely monitoring forest conversion in sensitive areas, i.e. areas at the forest frontier; a number of municipalities were selected according to their vulnerability to forest conversion and prevention policies were implemented. For instance, from 2008 on, in the selected municipalities, rural credits were made conditional on proof of compliance with environmental regulations, which mainly consist in leaving a given percentage of land under forest in each rural establishment. Thus, we introduced a time dummy (year_04) which takes value 1 in 2004 and subsequent years. We have also crossed with other explanatory variables to analyze the differentiated effects of this program according to the characteristics of municipalities.

Figures 2-7 show that after 2004, deforestation has moved toward the MCAs with a high rate of forest and where the agricultural GDP is low. One can see that, focusing on the forest cover and on the agricultural GDP, the Brazilian Amazon is closer to a concentrated spatial distribution.

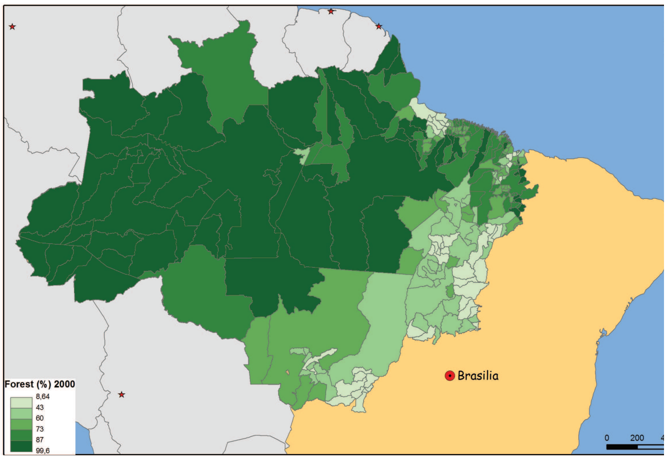


Figure 2: Percentage of forest in the MCAs of Brazilian Legal Amazon in 2000

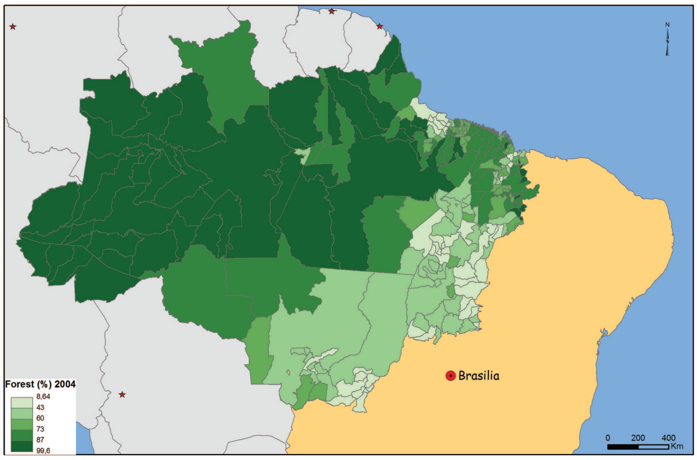


Figure 3: Percentage of forest in the MCAs of Brazilian Legal Amazon in 2004

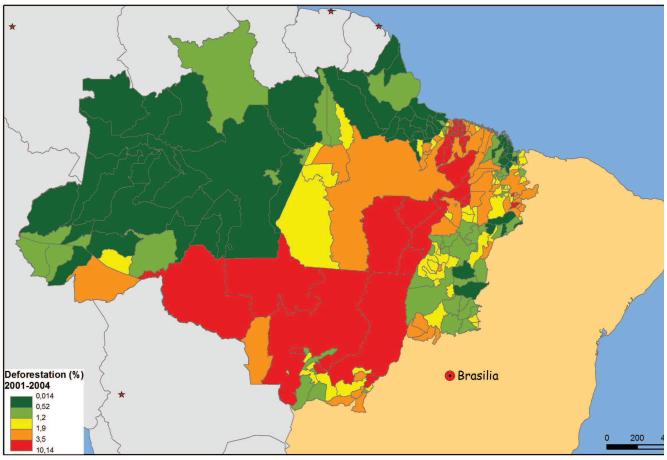


Figure 4: Percentage of deforestation in the MCAs of Brazilian Legal Amazon from 2001 to 2004

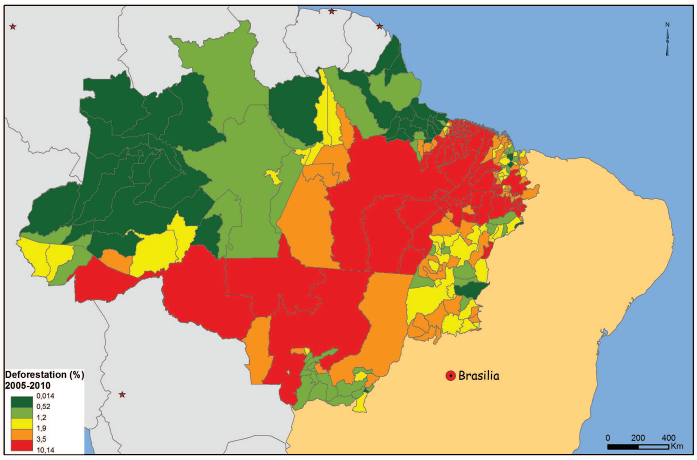


Figure 5: Percentage of deforestation in the MCAs of Brazilian Legal Amazon from 2005 to 2010

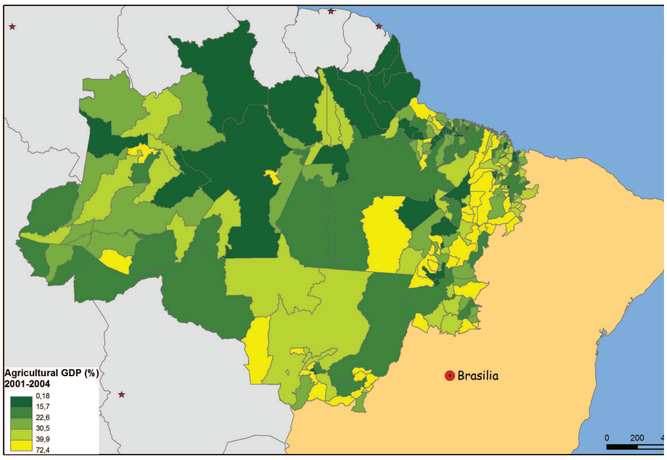


Figure 6: Percentage of agricultural GDP in the MCAs of Brazilian Legal Amazon from 2001 to 2004

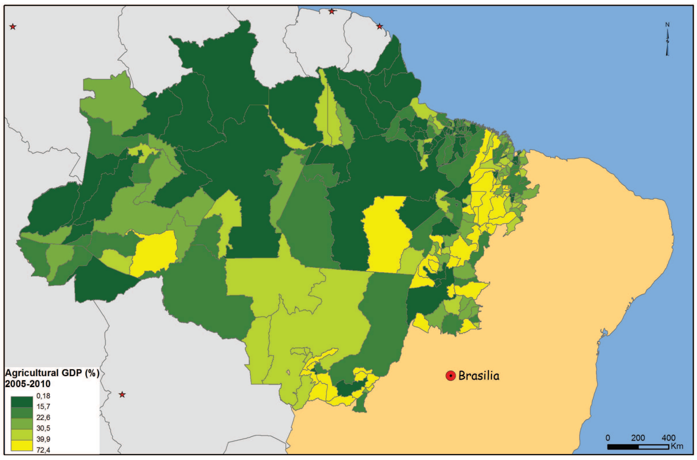


Figure 7: Percentage of agricultural GDP in the MCAs of Brazilian Legal Amazon from 2005 to 2010

4 Empirical Results

Our main empirical results are presented in Table 1 below. The presence of endogenous effects is confirmed by a significant value of ρ. In particular, $\rho > 0$ is in line with a general complementarity relation between deforestation in neighboring MCAs. Put differently, deforestation levels in a given MCA tend to be similar to those of its neighbors. Figures 4 and 5 show that deforestation is concentrated at the deforestation frontier (in southern Amazonia), but move more and more towards the north. Deforestation decisions being strategic complements, spatial concentration will tend to strengthen the dynamics of deforestation according to our theoretical predictions.

In the following the section, we discuss the results obtained. In Section 4.1, we discuss the role of the main traditional deforestation drivers, while in Section 4.2 we discuss the issue of local spillovers. In section 4.3, we present the results of global spillovers, the total effects in section 4.4 and we discuss the hypothesis of a non-linearity effect of rainfall, GDP and forest cover in section 4.5.

4.1 Main effects: the traditional deforestation drivers

First, the time lag coefficient of deforestation is positive ($\alpha > 0$) and significant at the 1% level, meaning that past deforestation in one municipality tends to favor current forest clearing. This result confirms the fact that deforestation is relatively persistent over time and is a process exhibiting a temporal inertia.

Table 1: Estimation results with spatial models with different weights matrix

	DSDM $1/d$	DSDM $\mathrm{c}1/d^2$	DSDM $1/d^3$
L.cleared	0.181***	0.179***	0.176***
	(0.0123)	(0.0122)	(0.0122)
gdpcap	-0.289	0.339	1.273
	(3.446)	(3.544)	(3.543)
gdpagric	87.45	108.4	144.8**
	(67.52)	(67.94)	(66.80)
pop_dens	-0.0191	0.111	0.0967
	(0.546)	(0.579)	(0.581)
forest	0.00676***	0.00885***	0.0118***
	(0.00260)	(0.00290)	(0.00307)
cattle	0.0000481	0.0000630*	0.0000701*
	(0.0000340)	(0.0000357)	(0.0000377)
precip	0.0816***	0.195***	0.367***
	(0.0312)	(0.0478)	(0.0628)
year2004	-243.6	-89.82	-16.20
	(183.1)	(74.35)	(50.62)
gdpcap04	1.852	1.580	0.919
	(1.998)	(2.149)	(2.234)
gdpagri04	-128.0***	-122.8***	-111.4**
	(46.85)	(47.25)	(47.10)
pop_dens04	-0.0228	-0.0276	-0.0271
	(0.0556)	(0.0601)	(0.0611)
forest04	-0.000983***	-0.000934***	-0.000892***
	(0.000225)	(0.000229)	(0.000232)
cattle04	-0.000217***	-0.000217***	-0.000216***
	(0.00000775)	(0.00000814)	(0.00000834)
precip04	-0.0480*	-0.0963**	-0.158***
	(0.0284)	(0.0428)	(0.0573)
Wx			
gdpcap	-10.81	-8.383	-11.70
	(21.54)	(9.816)	(7.853)
gdpagric	-36.98	61.31	31.37
	(452.3)	(176.7)	(116.4)
pop_dens	4.468	0.378	0.0439
	(2.778)	(1.106)	(0.735)
forest	0.00776	-0.0126	-0.0180**
	(0.0223)	(0.0120)	(0.00838)
cattle	0.000341	-0.000112	-0.000215
	(0.000282)	(0.000252)	(0.000226)
precip	-0.179***	-0.259***	-0.410***
	(0.0611)	(0.0598)	(0.0687)
gdpcap04	-0.279	-2.134	0.897
	(15.27)	(5.999)	(4.743)
gdpagri04	643.7	325.3**	182.3**
	(419.4)	(149.4)	(92.05)
pop_dens04	-0.548	-0.0485	-0.0101
	(0.417)	(0.135)	(0.0859)
forest04	0.00306*	0.00117	0.000974*
	(0.00164)	(0.000734)	(0.000568)
cattle04	-0.0000174	0.0000701	0.0000560
	(0.000147)	(0.0000694)	(0.0000533)
precip04	0.125**	0.132**	0.172***
	(0.0615)	(0.0540)	(0.0619)
ρ	0.585***	0.345***	0.231***
	(0.112)	(0.0620)	(0.0428)
sigma2_e	17091.2***	16959.6***	16788.8***
	(461.3)	(460.2)	(456.3)
Observations	2232	2232	2232
AIC	27995.0	27989.8	27969.6
BIC	28377.6	28372.4	28352.2
Log lik.	-13930.5	-13927.9	-13917.8

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, looking at the β_1s, we observe that as expected, more cattle ranching, area of natural forest, percentage of agricultural GDP or rainfall in a given MCA is associated with higher levels of deforestation. However, note that this relationship is reversed after 2004, when the PPCDAm program was implemented. This is because, by aiming at fighting forest conversion in the Legal Amazon, this program was designed to specifically target high risk municipalities. Hence, when interacting cattle, area of natural forest, percentage of agricultural GDP or rainfall, with that of year2004 (cattle04), we observe that the associated coefficient is now negative and significant to the 1% level. This result gives the insight that the PPCDAM managed to target efficiently the counties in which deforestation drivers and thus deforestation pressure were the most important.

4.2 Local Spillovers : spatially lagged explanatory variables

Local spillovers (β_2s) are presented in the second part of Table 1. These effects translate how the characteristics of neighbors affect deforestation in a given MCA. As we can see, more hectares of primary forest and higher rainfall in neighboring areas tend to be associated with lower deforestation rates in each MCA. This result is not really surprising: counties surrounded by MCA with larger forest cover tend to be "protected" from deforestation pressures. In contrast, counties located at the deforestation frontier, are surrounded by other counties already experiencing large levels of deforestation and then lower forest cover, which increase deforestation pressures in the neighborhood.

This relationship is reversed after the implementation of PPCDAm program. Indeed, after 2004, it became more difficult to clear forests for economic activities in MCA with high rates of deforestation (equivalently low remaining forest cover). This result suggests that there was a leakage of deforestation to the MCA with low deforestation rates. Moreover, this result gives this insight that public policy implementation tends to completely modify the nature of spatial interactions of deforestation. This tends to show that the nature of spatial interactions related to socio-economic factors are rather different than the one related to policy implementation. This result is in line with Ewers and Rodrigues (2008) who have shown that the establishment of protected areas can, in some cases, simply lead to a displacement of deforestation towards unprotected areas.

When looking at figures 2, 3, 6 and 7, one can see that the South East and East regions are the ones where those spatial spillovers are the most detrimental to forest loss. Zones where deforestation pressure is the most important are also the ones where spatial interactions have the most important effects.

4.3 Global Spillovers : Indirect effects

The indirect effects associated with forest area and rainfall variable are significant and negative, suggesting they are factors of substitutability: larger forest area or rainfall that increase deforestation in a given MCA (direct effects) also leads to a reduction of deforestation in all others MCAs (global spillovers).

However, after 2004 a high level of percentage of agricultural GDP (or rainfall) in a particular MCA favors deforestation in all others MCAs. In other words, a high level of percentage of agricultural GDP (or rainfall) in a MCA helps to reduce deforestation in this MCA (direct effect), but at the same time it leads to an increase in deforestation in all other MCAs (global spillovers). This program contributed to displace deforestation to targeted MCAs with high percentage of agricultural GDP to non-targeted MCAs with relatively low percentage of agricultural GDP, via a leakage effect.

4.4 Total effects

The total effect associated with cattle and rainfall are significant and negative. This means that the increase of rainfall in one MCA or cattle in one targeted MCA will lead an decrease of deforestation in all other MCAs. Therefore, policies based on these two variables could affect all Brazilian Amazon.

4.5 Robustness check: looking for non-linearities

Economics theory and previous studies suggest that some variables may exhibit non linearities in their on deforestation. As a robustness check of our previous results, we thus perform some further regressions introducing the square of three key variables: forest area (testing for the forest transition hypothesis), GDP (testing for an Environmental Kuznets Curve), and rainfall. The results of nonlinearity test are shown in Table I.3 and direct, indirect and total effects in Table I.4 (See Appendix).

First, we focus on the impact of the forest area. This idea is related to forest transition hypothesis. According to the hypothesis of the forest transition, deforestation progresses as agricultural rent is above the forest rent. Since forest rent increases with the reduction of the forest cover (increasing the opportunity cost of reducing the forest cover and reducing goods and services of the forest), the increase of deforestation provides a very important feedback that helps to stabilize forest cover (Angelsen, 2007). Therefore deforestation and forest cover are related by an U-shaped relationship. According to our results, the total effect of forest is negative and significant while forest2 (forest area squared) has a significant and positive effect. This means that the forest area has a positive effect on deforestation when it exceeds 77,413km^2 and a negative effect otherwise. In terms of public policy, these results suggest that the actions against deforestation should put more effort in the MCA with forest area above 77,413km^2, who are likely to experience larger deforestation pressures.

Second, the Environmental Kuznets Curve (EKC) hypothesis relates deforestation and income by an inverted U-shaped relationship (Culas, 2012; Choumert et al., 2012). According to our results, the main effects (β_1) and direct effects do not exhibit an EKC for deforestation: GDP per capita and its quadratic term have the correct sign, but are not significant. As Direct effects measure the impact of explanatory variables of MCA on its own deforestation, we can conclude that our study does not support the EKC hypothesis. Similar results were found in the literature (Choumert et al., 2012). However, local spillovers (β_2) and indirect effects of GDP is negative and significant while the quadratic term is significant and positive. This result gives the insight of an inverse spatial EKC for deforestation: GDP of a particular MCA in related to deforestation of all others municipalities by U-shaped form. In other words, the GDP of a given MCA has negative influence on the deforestation in all others municipalities up to a certain threshold (18.29 R $) from which its impact becomes positive. This result seems logical since a high GDP in a given MCA (given that agricultural is the main driver of GDP in the Amazon's) may be perceived by others MCA as a signal of their future level of gdp if they increase their levels of deforestation.

Finally, as expected, rainfall has a positive effect on deforestation while its quadratic term has a negative effect. Indeed, too much rainfall does not favor agricultural activities.

Table 2: Direct, Indirect, and Total effects

	DSDM $1/d$	DSDM $c1/d^2$	DSDM $1/d^3$
Direct			
gdpcap	-0.147	0.378	1.019
	(3.738)	(3.818)	(3.780)
gdpagric	90.56	114.2	150.4**
	(73.21)	(73.45)	(72.05)
pop_dens	0.0318	0.124	0.100
	(0.513)	(0.542)	(0.544)
forest	0.00739***	0.00911***	0.0116***
	(0.00237)	(0.00259)	(0.00273)
cattle	0.0000603*	0.0000682**	0.0000684**
	(0.0000331)	(0.0000330)	(0.0000334)
precip	0.0790**	0.188***	0.350***
	(0.0329)	(0.0495)	(0.0641)
year2004	-251.6	-92.73	-17.61
	(177.4)	(74.04)	(50.85)
gdpcap04	1.681	1.325	0.753
	(1.889)	(2.011)	(2.065)
gdpagri04	-124.2**	-116.6**	-105.7**
	(48.70)	(49.06)	(48.78)
pop_dens04	-0.0277	-0.0281	-0.0267
	(0.0551)	(0.0597)	(0.0606)
forest04	-0.000957***	-0.000911***	-0.000857***
	(0.000222)	(0.000222)	(0.000221)
cattle04	-0.000219***	-0.000218***	-0.000216***
	(0.00000824)	(0.00000830)	(0.00000836)
precip04	-0.0514*	-0.101**	-0.162***
	(0.0285)	(0.0413)	(0.0547)
Indirect			
gdpcap	-27.37	-11.22	-13.35
	(59.85)	(13.54)	(8.925)
gdpagric	-54.95	110.0	54.09
	(1337.1)	(264.1)	(142.8)
pop_dens	10.76	0.447	-0.00191
	(9.057)	(1.663)	(0.914)
forest	0.0229	-0.0163	-0.0205**
	(0.0677)	(0.0170)	(0.00958)
cattle	0.000958	-0.000160	-0.000273
	(0.000768)	(0.000370)	(0.000280)
precip	-0.337**	-0.285***	-0.405***
	(0.151)	(0.0656)	(0.0694)
year2004	-422.8	-49.12	-5.116
	(462.9)	(43.90)	(15.29)
gdpcap04	2.752	-2.544	1.336
	(40.82)	(8.048)	(5.180)
gdpagri04	1546.1	440.6**	207.1**
	(1254.0)	(212.2)	(104.6)
pop_dens04	-1.281	-0.0604	-0.00720
	(1.369)	(0.222)	(0.115)
forest04	0.00715	0.00137	0.00101
	(0.00535)	(0.00114)	(0.000742)
cattle04	-0.000428	-0.0000135	0.00000575
	(0.000460)	(0.0000942)	(0.0000598)
precip04	0.257	0.156***	0.179***
	(0.161)	(0.0587)	(0.0592)
Total			
gdpcap	-27.52	-10.84	-12.33
	(59.00)	(12.74)	(8.322)
gdpagric	35.61	224.3	204.5
	(1351.2)	(281.6)	(163.9)
pop_dens	10.80	0.570	0.0984
	(8.949)	(1.546)	(0.861)
forest	0.0303	-0.00719	-0.00886
	(0.0672)	(0.0161)	(0.00856)
cattle	0.00102	-0.0000921	-0.000205
	(0.000761)	(0.000363)	(0.000273)
precip	-0.258*	-0.0974***	-0.0556**
	(0.141)	(0.0329)	(0.0218)
year2004	-674.4	-141.9	-22.73
	(602.0)	(115.5)	(65.79)
gdpcap04	4.433	-1.219	2.089
	(40.77)	(7.808)	(4.804)
gdpagri04	1421.9	324.0	101.3
	(1270.9)	(229.0)	(122.0)
pop_dens04	-1.309	-0.0885	-0.0339
	(1.356)	(0.204)	(0.103)
forest04	0.00620	0.000461	0.000153
	(0.00534)	(0.00109)	(0.000686)
cattle04	-0.000647	-0.000232**	-0.000210***
	(0.000460)	(0.0000930)	(0.0000586)
precip04	0.206	0.0554	0.0174
	(0.152)	(0.0338)	(0.0203)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Discussion and Conclusions

Using a simple theoretical model and methods of spatial econometrics, this paper investigates the spatial interactions underlying the deforestation process in the Brazilian Amazon, as well as the most determinant variables in explaining these interactions. We show that complementarity tends to be the general pattern behind deforestation: the higher MCA i's neighbors' deforestation, the higher its own level of forest conversion will be. This result confirms previous results obtained by Robalino and Pfaff (2012) in Costa Rica. By analyzing the spillover effects associated with each explanatory variable, we additionally show that the variables that appear to be the strongest diffusion channels of deforestation are higher percentage of agricultural GDP and rainfall after 2004. In contrast, a high primary forest and rainfall (before 2004) tend to have negative spillover effects on deforestation. It also appears that the primary forest, the precipitation, the percentage of agricultural GDP (after 2004) and rainfall (after 2004) lead to situations of substitutability. Indeed, when these variables have a positive influence on deforestation in the MCA, they have in the same time a negative spillover effect on deforestation.

Our results also suggest that the program has helped reduce deforestation. In fact, before 2004, the primary forest, rainfall and cattle were factors promoting deforestation. But after 2004, these variables have negatively influenced deforestation. Yet this program has also caused leakage of deforestation toward municipalities with low deforestation rates. For instance, our results suggest that, after the implementation of the program in 2004, an increase in percentage of agricultural GDP in a municipality lead to an increase of deforestation in all other municipalities (spillover effects). Therefore, to be fully effective, policies against deforestation must take into account the spillover effects. Indeed these effects can make policies more effective when they generate synergy effects or less effective when they generate leakages.

Finally, our results supported the forest transition hypothesis. Indeed, we show that the primary forest has a positive effect on deforestation when it exceeds 77,413km2 and a negative effect otherwise. The policies aiming to fight against deforestation tend to focus on regions with high rates of deforestation. However, this result suggests to also focus on areas with large primary forest, as they may experience stronger deforestation pressure in the near future. Moreover, these regions have the advantage of having a pristine biological and ecological ecosystem.

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Appendices

A Value of the simulation parameters

Table A.1

$\overline{X}$		5
$\underline{X}$		0
α_{ij}	Low interactions	0.05
	High interactions	0.1
D_i^*		$\in [-2; 9]$

B Illustration of concentration and dissemination cases

Figure B.1: **Maps of counties for the concentration and the dissemination cases**

Concentration

$\bar{x}$	$\bar{x}$	$\bar{x}$	$\underline{x}$	$\underline{x}$
$\bar{x}$	$\bar{x}$	$\bar{x}$	$\underline{x}$	$\underline{x}$
$\bar{x}$	$\bar{x}$	$\bar{x}$	$\underline{x}$	$\underline{x}$
$\bar{x}$	$\bar{x}$	$\underline{x}$	$\underline{x}$	$\underline{x}$
$\bar{x}$	$\bar{x}$	$\underline{x}$	$\underline{x}$	$\underline{x}$

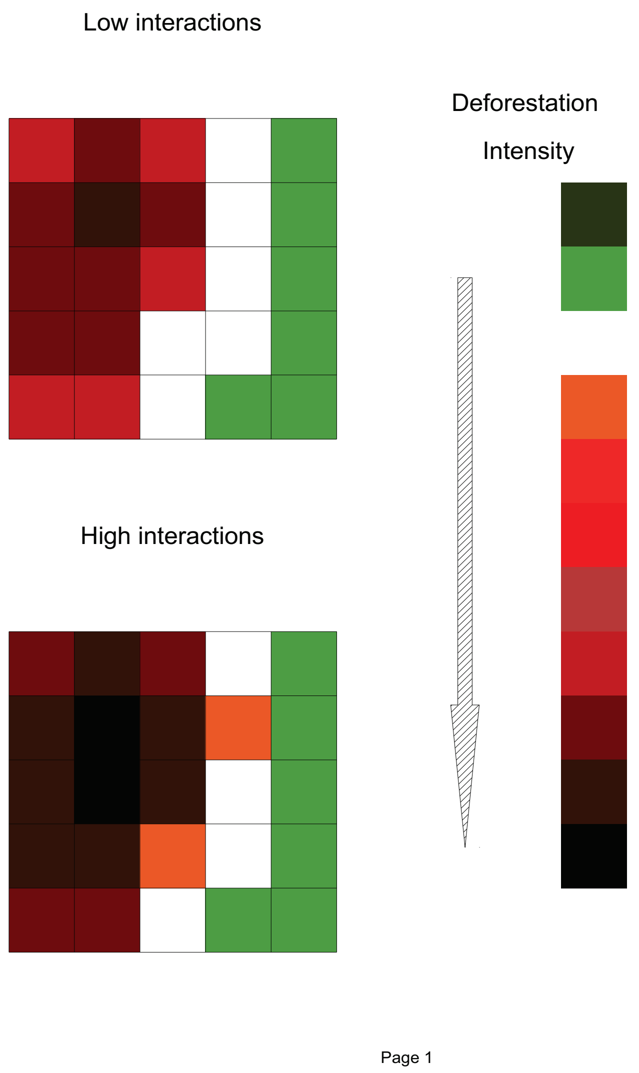
Dissemination

$\bar{x}$	$\underline{x}$	$\bar{x}$	$\underline{x}$	$\bar{x}$
$\underline{x}$	$\bar{x}$	$\underline{x}$	$\bar{x}$	$\underline{x}$
$\bar{x}$	$\underline{x}$	$\bar{x}$	$\underline{x}$	$\bar{x}$
$\underline{x}$	$\bar{x}$	$\underline{x}$	$\bar{x}$	$\underline{x}$
$\bar{x}$	$\underline{x}$	$\bar{x}$	$\underline{x}$	$\underline{x}$

Page 1

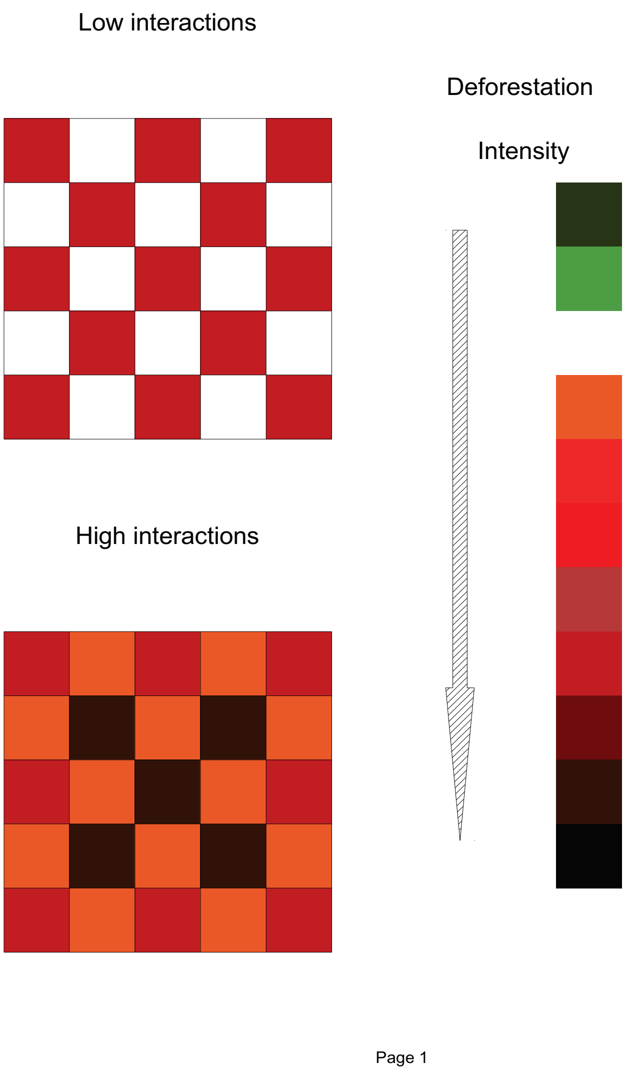
C Complementarity and Concentration

Figure C.1: **Deforestation map in case of complementarity and counties concentration**



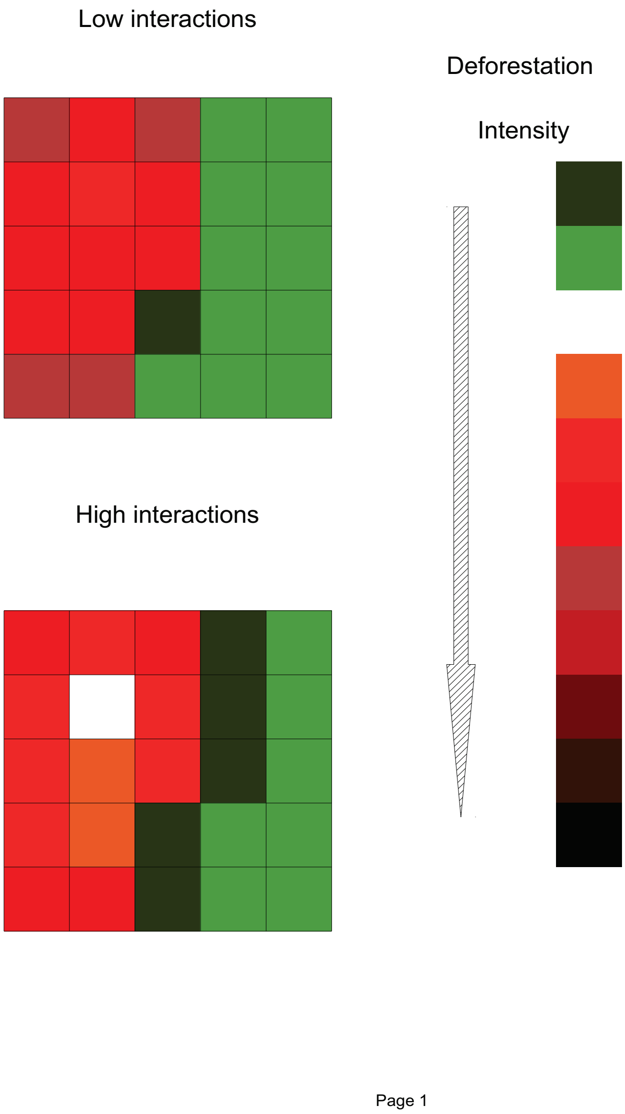
D Complementarity and Dissemination

Figure D.1: **Deforestation map in case of complementarity and counties dissemination**



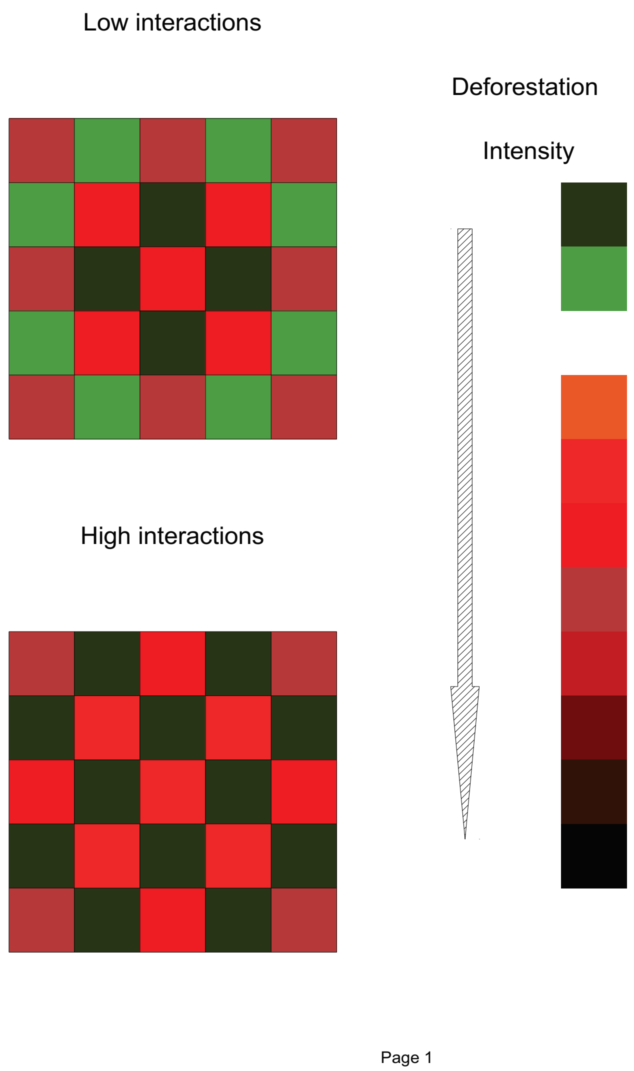
E Substitutability and Concentration

Figure E.1: **Deforestation map in case of substitutability and counties concentration**



F Substitutability and Dissemination

Figure F.1: **Deforestation map in case of substitutability and counties dissemination**



G Variables description

Table G.1: Main variables description

Variable	Definition	Source
cleared	Hectares of land cleared	Prodes
gdpcap	GDP per capita (R$ of 2000)	IPEAdata
pop_dens	Population density (Total MCA population/MCA area)	IPEAdata
forest	Surface of forest in the MCA in hectares	Prodes
corn	Hectares of land under corn	IBGE - Agricultural Census
cotton	Hectares of land under cotton	IBGE - Agricultural Census
soy	Hectares of land under soy	IBGE - Agricultural Census
sugarcane	Hectares of land under sugarcane	IBGE - Agricultural Census
precip	Average yearly precipitations in milliliters	IPEAdata

H Summary statistics

Table H.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
cleared	84.463	404.889	0	6359.7
gdpcap	3.061	3.423	0.757	43.849
gdpcap2	21.083	94.782	0.573	1922.775
gdpagric	0.273	0.146	0.001	0.792
pop_dens	41.777	193.461	0.092	2617.719
forest	13105.184	37132.661	0	320163.502
forest2	1550024421.04	8458476753.388	0	102504669184
cattle	275047.006	1051410.95	0	11842073
precip	2088.608	605.804	856.349	4025.641
precip2	4729132.547	2687750.021	733334.125	16205786
an04	0.6	0.49	0	1
gdpcap04	1.948	3.103	0	40.443
gdpagri04	0.158	0.171	0	0.729
pop_dens04	25.956	156.921	0	2617.719
forest04	7669.253	28851.156	0	317854.594
cattle04	177126.94	885146.937	0	11842073
precip04	1277.97	1155.26	0	3598.18
N		2480		

I Empirical Results

Table I.1: Comparison of spatial models

Model	SAR	SDM	SEM	SAC	DSAR	DSDM
gdpcap	-0.307	-0.192	0.267	-0.00171	-0.894	-0.289
	(4.048)	(4.322)	(4.242)	(4.182)	(3.207)	(3.446)
gdpagric	178.7**	174.8**	198.7**	179.4**	80.60	87.45
	(80.88)	(87.99)	(86.08)	(84.83)	(62.23)	(67.52)
pop_dens	0.463	0.621	0.582	0.546	0.0785	-0.0191
	(0.656)	(0.683)	(0.680)	(0.672)	(0.514)	(0.546)
forest	0.0168***	0.0165***	0.0166***	0.0166***	0.00830***	0.00676***
	(0.00323)	(0.00356)	(0.00337)	(0.00333)	(0.00232)	(0.00260)
cattle	0.000139***	0.000133***	0.000140***	0.000139***	0.0000538	0.0000481
	(0.0000377)	(0.0000387)	(0.0000384)	(0.0000379)	(0.0000329)	(0.0000340)
precip	0.00550	0.0730*	0.0356	0.0306	0.00544	0.0816***
	(0.0215)	(0.0391)	(0.0328)	(0.0317)	(0.0168)	(0.0312)
year2004	161.8***	244.3	233.4***	244.8***	113.1***	-243.6
	(42.79)	(240.1)	(89.54)	(70.62)	(32.66)	(183.1)
gdpcap04	7.203***	3.068	3.700	4.117	3.409**	1.852
	(2.367)	(2.803)	(2.586)	(2.546)	(1.691)	(1.998)
gdpagri04	-202.7***	-239.2***	-237.1***	-223.7***	-96.43**	-128.0***
	(61.73)	(64.12)	(62.97)	(62.19)	(44.69)	(46.85)
pop_dens04	-0.106	-0.0865	-0.0888	-0.0900	-0.0539	-0.0228
	(0.0745)	(0.0777)	(0.0768)	(0.0758)	(0.0526)	(0.0556)
forest04	-0.00114***	-0.00201***	-0.00164***	-0.00153***	-0.000606***	-0.000983***
	(0.000271)	(0.000307)	(0.000289)	(0.000286)	(0.000197)	(0.000225)
cattle04	-0.000233***	-0.000229***	-0.000233***	-0.000231***	-0.000218***	-0.000217***
	(0.0000104)	(0.0000107)	(0.0000106)	(0.0000104)	(0.00000750)	(0.00000775)
precip04	-0.0288*	-0.0852**	-0.0391*	-0.0367*	-0.0203*	-0.0480*
	(0.0153)	(0.0376)	(0.0225)	(0.0215)	(0.0121)	(0.0284)
L.cleared					0.184***	0.181***
					(0.0122)	(0.0123)
ρ	0.851***	0.873***		0.709***	0.558***	0.585***
	(0.0402)	(0.0365)		(0.0774)	(0.0946)	(0.112)
λ			0.880***	0.814***		
			(0.0340)	(0.0542)		
Variance						
sigma2_e	34924.2***	33953.5***	34373.2***	37345.7***	17335.6***	17091.2***
	(995.6)	(968.4)	(980.2)	(961.3)	(467.6)	(461.3)
Wx						
gdpcap		-24.33				-10.81
		(29.08)				(21.54)
gdpagric		1075.5*				-36.98
		(577.8)				(452.3)
pop_dens		-2.281				4.468
		(3.513)				(2.778)
forest		-0.0228				0.00776
		(0.0308)				(0.0223)
cattle		0.000229				0.000341
		(0.000338)				(0.000282)
precip		-0.0623				-0.179***
		(0.0770)				(0.0611)
gdpcap04		30.71				-0.279
		(21.30)				(15.27)
gdpagri04		-686.8				643.7
		(553.6)				(419.4)
pop_dens04		0.0344				-0.548
		(0.567)				(0.417)
forest04		0.00655***				0.00306*
		(0.00227)				(0.00164)
cattle04		0.0000418				-0.0000174
		(0.000204)				(0.000147)
precip04		0.0573				0.125**
		(0.0804)				(0.0615)
Observations	2480	2480	2480	2480	2232	2232
AIC	33047.3	33005.2	33012.9	32969.9	27924.5	27917.0
BIC	33134.6	33162.2	33100.1	33062.9	28015.9	28076.9
Log lik.	-16508.7	-16475.6	-16491.5	-16468.9	-13946.2	-13930.5

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table I.2: Estimation results DSDM : fixed effects vs random effects

Model	Fixed effects	Random effects
L.cleared	0.181***	0.357***
	(0.0123)	(0.0122)
gdpcap	-0.289	-3.810**
	(3.446)	(1.843)
gdpagric	87.45	153.8***
	(67.52)	(43.53)
pop_dens	-0.0191	0.0265
	(0.546)	(0.0336)
forest	0.00676***	0.00255***
	(0.00260)	(0.000203)
cattle	0.0000481	0.000272***
	(0.0000340)	(0.00000786)
precip	0.0816***	0.0481*
	(0.0312)	(0.0270)
year2004	-243.6	-295.9
	(183.1)	(207.3)
gdpcap04	1.852	1.775
	(1.998)	(2.310)
gdpagri04	-128.0***	-109.6**
	(46.85)	(54.00)
pop_dens04	-0.0228	-0.0230
	(0.0556)	(0.0400)
forest04	-0.000983***	-0.00109***
	(0.000225)	(0.000241)
cattle04	-0.000217***	-0.000215***
	(0.00000775)	(0.00000803)
precip04	-0.0480*	-0.0231
	(0.0284)	(0.0327)
Constant		302.2
		(189.5)
Wx		
gdpcap	-10.81	1.562
	(21.54)	(14.19)
gdpagric	-36.98	-770.7*
	(452.3)	(421.2)
pop_dens	4.468	0.336
	(2.778)	(0.334)
forest	0.00776	-0.00539***
	(0.0223)	(0.00144)
cattle	0.000341	0.0000997
	(0.000282)	(0.000145)
precip	-0.179***	-0.143**
	(0.0611)	(0.0626)
gdpcap04	-0.279	-4.393
	(15.27)	(17.10)
gdpagri04	643.7	851.4*
	(419.4)	(467.0)
pop_dens04	-0.548	-0.248
	(0.417)	(0.390)
forest04	0.00306*	0.00171
	(0.00164)	(0.00177)
cattle04	-0.0000174	-0.0000723
	(0.000147)	(0.000171)
precip04	0.125**	0.104
	(0.0615)	(0.0703)
ρ	0.585***	0.469***
	(0.112)	(0.115)
sigma2_e	17091.2***	-148.1***
	(461.3)	(2.220)
sigma_a		7.56e-08
		(16.32)
Observations	2232	2232
AIC	27917.0	28711.2
BIC	28076.9	28882.6
Log lik.	-13930.5	-14325.6

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table I.3: Nonlinearity Test

	DSDM : GDP	DSDM : Rainfall	DSDM : Forest	DSDM : GDP, Rainfall and Forest
L.cleared	0.175***	0.173***	0.175***	0.174***
	(0.0122)	(0.0122)	(0.0124)	(0.0124)
gdpcap	4.219	1.487	1.465	4.441
	(7.306)	(3.532)	(3.546)	(7.307)
gdpcap2	-0.0881			-0.0869
	(0.158)			(0.158)
gdpagric	139.2**	153.2**	140.5**	136.7**
	(68.00)	(66.59)	(66.92)	(68.11)
pop_dens	0.113	0.0931	0.110	0.120
	(0.581)	(0.579)	(0.581)	(0.580)
forest	0.0119***	0.0125***	0.0121**	0.0125**
	(0.00307)	(0.00307)	(0.00551)	(0.00550)
cattle	0.0000686*	0.0000714*	0.0000725*	0.0000711*
	(0.0000377)	(0.0000376)	(0.0000385)	(0.0000385)
precip	0.370***	1.102***	0.358***	0.458***
	(0.0628)	(0.188)	(0.0630)	(0.0869)
an04	-1.010	-20.47	-21.52	-11.41
	(51.27)	(50.66)	(50.70)	(51.41)
gdpcap04	0.574	0.671	0.865	0.439
	(2.302)	(2.227)	(2.238)	(2.306)
gdpagri04	-114.7**	-110.7**	-110.6**	-114.9**
	(47.09)	(46.93)	(47.15)	(47.12)
pop_dens04	-0.0289	-0.0265	-0.0274	-0.0291
	(0.0611)	(0.0609)	(0.0611)	(0.0611)
forest04	-0.000899***	-0.000885***	-0.000920***	-0.000928***
	(0.000233)	(0.000231)	(0.000262)	(0.000262)
cattle04	-0.000216***	-0.000215***	-0.000216***	-0.000216***
	(0.00000834)	(0.00000831)	(0.00000870)	(0.00000869)
precip04	-0.160***	-0.176***	-0.154***	-0.161***
	(0.0573)	(0.0573)	(0.0575)	(0.0576)
precip2		-0.000154***		-0.0000189
		(0.0000372)		(0.0000117)
forest2			-3.02e-09	-3.74e-09
			(1.58e-08)	(1.58e-08)
Wx				
gdpcap	-34.15**	-10.34	-11.31	-36.45***
	(13.82)	(7.832)	(7.851)	(13.88)
gdpcap2	0.934**			1.051**
	(0.468)			(0.472)
gdpagric	45.36	-15.43	18.62	38.88
	(116.7)	(116.7)	(116.5)	(116.8)
pop_dens	0.128	0.0447	-0.0163	-0.0395
	(0.737)	(0.737)	(0.736)	(0.740)
forest	-0.0189**	-0.0185**	-0.0355***	-0.0351***
	(0.00838)	(0.00837)	(0.0133)	(0.0133)
cattle	-0.000196	-0.000187	-0.000191	-0.000189
	(0.000226)	(0.000226)	(0.000226)	(0.000227)
precip	-0.408***	-1.162***	-0.399***	-0.420***
	(0.0687)	(0.201)	(0.0690)	(0.0706)
gdpcap04	2.910	1.358	0.444	2.718
	(4.852)	(4.727)	(4.751)	(4.858)
gdpagri04	170.0*	202.3**	196.7**	177.0*
	(92.20)	(91.98)	(92.33)	(92.54)
pop_dens04	-0.0171	0.00363	0.00304	0.0125
	(0.0862)	(0.0864)	(0.0862)	(0.0870)
forest04	0.000952*	0.00108*	0.00138**	0.00124**
	(0.000568)	(0.000572)	(0.000615)	(0.000619)
cattle04	0.0000521	0.0000444	0.0000697	0.0000656
	(0.0000533)	(0.0000532)	(0.0000538)	(0.0000538)
precip04	0.169***	0.187***	0.166***	0.174***
	(0.0619)	(0.0621)	(0.0621)	(0.0625)
precip2		0.000158***		
		(0.0000407)		
forest2			0.000000160*	0.000000152*
			(8.82e-08)	(8.83e-08)
rho	0.228***	0.225***	0.227***	0.224***
	(0.0429)	(0.0429)	(0.0429)	(0.0430)
sigma2_e	16762.2***	16667.9***	16768.7***	16722.5***
	(455.5)	(452.9)	(455.7)	(454.3)
Observations	2232	2232	2232	2232
AIC	27975.6	27962.5	27976.3	27987.5
BIC	28386.8	28373.6	28387.4	28450.1
Log lik.	-13915.8	-13909.2	-13916.1	-13912.8

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table I.4: Nonlinearity Test : Direct, Indirect and Total effects

	DSDM : GDP	DSDM : Rainfall	DSDM : Forest	DSDM : GDP, Rainfall and Forest
Direct				
gdpcap	3.123	1.237	1.163	3.300
	(7.955)	(3.810)	(3.829)	(7.847)
gdpcap2	-0.0495			-0.0429
	(0.164)			(0.164)
gdpagric	142.4**	157.4**	146.2**	139.5**
	(64.01)	(69.94)	(70.17)	(63.81)
pop_dens	0.243	0.101	0.116	0.238
	(0.548)	(0.545)	(0.546)	(0.544)
forest	0.0117***	0.0124***	0.0117**	0.0121**
	(0.00292)	(0.00276)	(0.00500)	(0.00533)
cattle	0.0000619*	0.0000719**	0.0000662*	0.0000609*
	(0.0000362)	(0.0000340)	(0.0000376)	(0.0000345)
precip	0.352***	1.062***	0.339***	0.436***
	(0.0603)	(0.191)	(0.0614)	(0.0794)
an04	-4.779	-23.64	-24.67	-8.201
	(47.63)	(47.25)	(47.64)	(49.58)
gdpcap04	0.639	0.692	0.835	0.372
	(2.409)	(2.289)	(2.267)	(2.211)
gdpagri04	-105.6**	-101.5**	-101.2**	-110.7**
	(47.47)	(46.32)	(46.85)	(47.07)
pop_dens04	-0.0433	-0.0297	-0.0307	-0.0487
	(0.0568)	(0.0578)	(0.0581)	(0.0571)
forest04	-0.000851***	-0.000837***	-0.000854***	-0.000860***
	(0.000245)	(0.000250)	(0.000267)	(0.000235)
cattle04	-0.000217***	-0.000218***	-0.000216***	-0.000215***
	(0.00000769)	(0.00000723)	(0.00000804)	(0.00000847)
precip04	-0.146***	-0.161***	-0.139**	-0.155***
	(0.0546)	(0.0556)	(0.0548)	(0.0584)
precip2		-0.000149***		-0.0000186*
		(0.0000370)		(0.0000105)
forest2			3.10e-09	6.21e-10
			(1.61e-08)	(1.70e-08)
Indirect				
gdpcap	-44.12**	-14.11	-15.39	-44.67***
	(17.50)	(9.843)	(9.914)	(15.80)
gdpcap2	1.189*			1.308**
	(0.609)			(0.569)
gdpagric	99.64	17.97	57.74	92.35
	(134.6)	(139.1)	(141.3)	(136.8)
pop_dens	0.207	0.0983	0.0280	-0.0927
	(0.839)	(0.834)	(0.833)	(0.815)
forest	-0.0214**	-0.0201**	-0.0413***	-0.0406***
	(0.0101)	(0.00942)	(0.0153)	(0.0156)
cattle	-0.000221	-0.000222	-0.000212	-0.000208
	(0.000249)	(0.000277)	(0.000250)	(0.000276)
precip	-0.399***	-1.139***	-0.392***	-0.389***
	(0.0643)	(0.202)	(0.0645)	(0.0688)
an04	-0.768	-5.926	-6.211	-2.086
	(14.05)	(13.47)	(13.78)	(13.18)
gdpcap04	4.296	2.329	1.267	4.096
	(6.160)	(5.715)	(5.925)	(6.149)
gdpagri04	184.3*	225.1**	216.9**	180.2*
	(110.3)	(102.4)	(103.9)	(109.0)
pop_dens04	-0.0281	-0.00279	-0.00413	0.0152
	(0.0982)	(0.100)	(0.0994)	(0.0984)
forest04	0.000927	0.00111	0.00144*	0.00122
	(0.000743)	(0.000693)	(0.000820)	(0.000748)
cattle04	0.00000898	0.000000347	0.0000290	0.0000276
	(0.0000674)	(0.0000652)	(0.0000682)	(0.0000684)
precip04	0.158***	0.174***	0.156***	0.171***
	(0.0576)	(0.0583)	(0.0572)	(0.0652)
precip2		0.000155***		-0.00000520
		(0.0000399)		(0.00000336)
forest2			0.000000188*	0.000000185*
			(0.000000108)	(0.000000106)
Total				
gdpcap	-41.00**	-12.87	-14.23	-41.37***
	(17.92)	(9.675)	(9.764)	(15.04)
gdpcap2	1.139*			1.265**
	(0.600)			(0.568)
gdpagric	242.1*	175.4	204.0	231.8*
	(143.0)	(137.2)	(137.7)	(139.4)
pop_dens	0.451	0.199	0.144	0.145
	(0.869)	(0.837)	(0.834)	(0.786)
forest	-0.00966	-0.00765	-0.0296**	-0.0285**
	(0.00892)	(0.00848)	(0.0146)	(0.0142)
cattle	-0.000159	-0.000150	-0.000146	-0.000147
	(0.000244)	(0.000270)	(0.000245)	(0.000271)
precip	-0.0478**	-0.0779	-0.0528**	0.0472
	(0.0233)	(0.0603)	(0.0224)	(0.0589)
an04	-5.546	-29.56	-30.88	-10.29
	(61.49)	(60.55)	(61.24)	(62.42)
gdpcap04	4.936	3.022	2.102	4.469
	(5.549)	(5.083)	(5.286)	(5.636)
gdpagri04	78.67	123.6	115.7	69.50
	(120.9)	(113.2)	(114.8)	(113.4)
pop_dens04	-0.0714	-0.0325	-0.0348	-0.0335
	(0.0942)	(0.0947)	(0.0939)	(0.0919)
forest04	0.0000766	0.000276	0.000584	0.000359
	(0.000728)	(0.000671)	(0.000797)	(0.000722)
cattle04	-0.000208***	-0.000217***	-0.000187***	-0.000188***
	(0.0000662)	(0.0000644)	(0.0000673)	(0.0000680)
precip04	0.0120	0.0135	0.0168	0.0166
	(0.0197)	(0.0208)	(0.0202)	(0.0201)
precip2		0.00000555		-0.0000238*
		(0.0000142)		(0.0000136)
forest2			0.000000191*	0.000000185*
			(0.000000114)	(0.000000109)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$